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Estimating the effect of domestic load and renewable supply variability on battery capacity requirements for decentralized micro-grids

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Abstract

Large battery banks are a commonly considered alternative for local storage of volatile energy supply in decentralized grid management. In this paper the hypothetical case of an isolated community of 15 houses with direct access to a nearby set of wind turbines and a backup grid connection (e.g. ex-urban hamlet) is being considered. The question arises as to what size of battery, relative to household average daily consumption, should be installed in order to avoid excessively fast aging of said battery bank, i.e. to avoid the need to replace it faster than standard expected battery lifetime. The basic technology of the batteries addressed in this study is lithium ion phosphate. A dynamic modeling process of aging is implemented, along with realistic wind power data and a stochastic model of domestic load, with variable morning/evening peaks, weekend and seasonal effects. It was found that simulations using domestic load profiles and variability predict a significant reduction in expected battery state of health, for comparable average loads, than standard load cycles used for industrial testing, and that increased variability in average domestic load has a minor effect on the speed of state of health reduction. Furthermore a region of high sensitivity to overall battery bank size can be observed, which subsides over approx. 200 hours of average household consumption.

Selection and Peer-review under responsibility of the Program Chairs.

Keywords: battery model; cell aging; variable load; wind power

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1. Introduction

The upcoming smart grid evolution increases renewable footprint and grid resilience by interconnecting micro-grids which include loads, storage and micro- to mid- size power plants. In northern latitudes, the most cost-efficient renewable (without specific geological conditions) is wind power. As part of an overall demographic trend, villages are becoming ever more compact, and the landscape outside cities is punctuated not only by isolated villages, but also by ex-urban groups of residential houses outside the suburban zone, but within a convenient distance to urban centres. These types of settlements provide nearly ideal candidates for micro-grid construction, given that they are often within visual distance of wind turbines, or have space for nearby wind park development. The question arises as to how such a micro-grid can be constructed, in order to make economic sense but also to appeal to the types of residents which choose to live far from cities. For example, theoretical autarky might be an important factor (ability to operate off-grid in case of catastrophic events). The critical factor is, however, the storage element which would achieve this independence in case of volatile supply. In this paper it is highlighted how the sizing of the storage element is affected by supply and load volatility, and especially what effect these factors would have on battery state of health (i.e. on aging), because autarky would be severely affected in case of premature battery aging. For this purpose a realistic use case (an exurban hamlet) was simulated based on a current battery technology able to operate over an order of 10^3 to 10^4 charge/discharge cycles: lithium ion.

Nomenclature

SOC [%]	State of charge – An expression of the present battery capacity as a percentage of maximum capacity
SOH [%]	State of health – An expression of the present condition of a battery compared to the ideal condition
EOL	End of life – When a battery's capacity reaches 80% of its nominal capacity it is commonly considered the end of life. This is an industry standard definition -it does not mean the battery will fully stop working at that point.
DOD [%]	Depth of discharge – The percentage of battery capacity that has been discharged expressed as a percentage of maximum capacity
C-Rate	A measure of the rate at which a battery is charged or discharged relative to its maximum capacity (e.g. 1C discharge current will discharge entire battery in 1 hour)[1,2]
[ADP]	ADP (Average Domestic Power Load) is a normalized power unit. 1 ADP equals the average power of one household.
[ADPh]	ADPh (Average Domestic Power Load hours) is a normalized energy unit. 1 ADPh equals the energy a household uses per hour.

2. Methodology

Within this paper the hypothetical case of a community with 15 households that have access to a nearby set of wind turbines and a grid connection is being considered. The annual energy delivered by the wind turbines exceeds the required energy by 20% as a safety factor. As energy storage a LiFePO4 battery is installed.

In order to predict the behavior of the battery in real life application a dynamic simulation model was created. The following section addresses the set-up and the assumptions made in the process.

2.1. Load and supply

It is assumed that the considered neighborhood has access to a set of wind turbines. The total energy that is supplied by them is scaled to match 120% of the total consumption of the households. This leads to theoretical autarchy with a 20% reserve as a safety factor to ensure against brownout when operating off grid. The data that was used represents the average over all Belgian onshore wind farms that are being monitored by ELIA and Belgian DSOs in the year 2013 with a sample time of 15 minutes (ELIA: http://www.elia.be/en/grid-data/power-generation/wind-power). Figure 2 shows the power supply over one year including the probability distribution, which shows seasonal effects.

The power consumption and load profile of the households is given by a stochastic load model. A day-period sinusoidal function, a constant load and saw tooth profile are used as a reference for comparison, given that they represent common load cycles in battery testing.

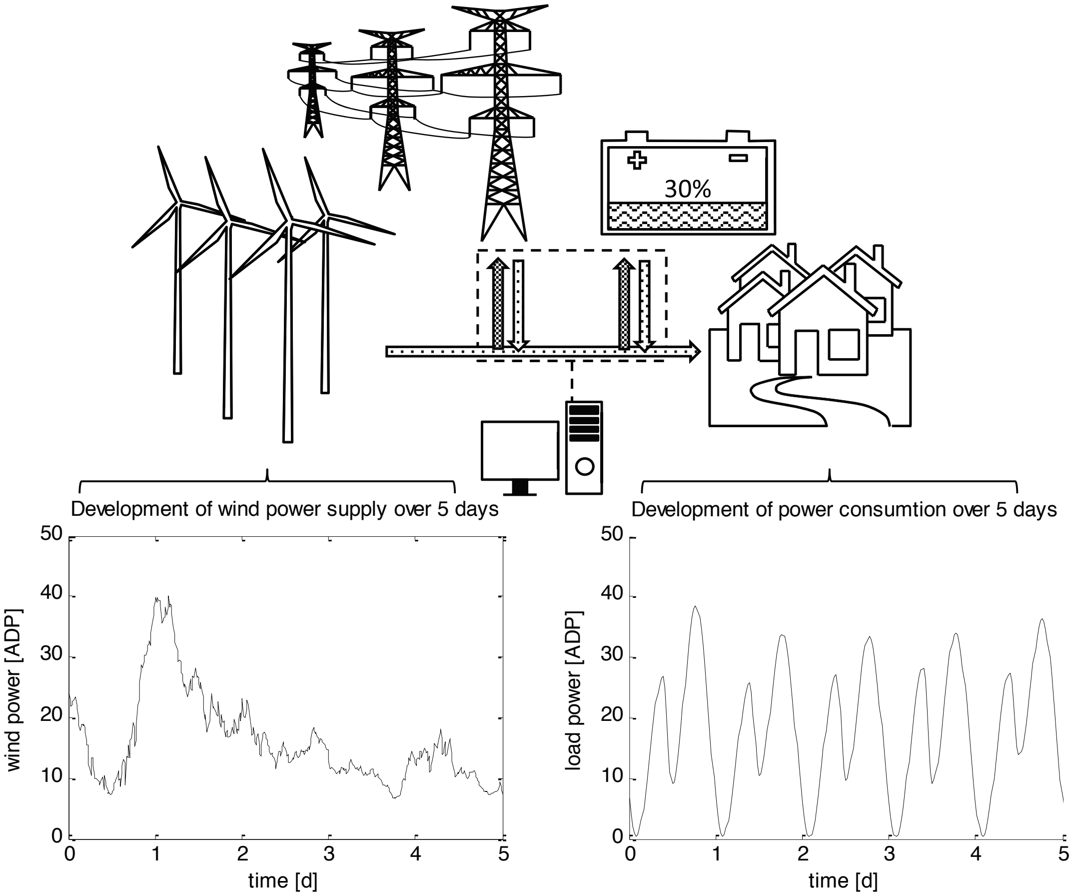

Figure 1: Configuration overview. Wind power and load power in detail. Load with medium variability. Power unit is ADP – average domestic power. 1 ADP equals the average power of one household. Thus the mean value of the load for 15 households is 15 ADP.

The load simulations were produced by a non-stationary random generating process, in which morning and afternoon peaks (09:30 and 18:30) alternated with relative lows at 02:00 and at 12:00, the night-time minimum being 10% of ADC and the noontime minimum random with minimum of 30% and maximum of average of the morning and afternoon peaks – 20% higher on weekend. The peaks were random with a controlled parameter for the variation of both, and an average afternoon to morning peak ratio of 30%. The momentary average load at points in between was fitted with a piecewise cubic polynomial. Additionally, the load profiles were multiplied by a seasonal adjustment factor, which varied from 0.8 to 1.2 and had a basic period of one year. The mean variability factor was chosen as to correspond, (for house number N=15) to a similar aggregate variability (with respect to yearly mean ADC) as that reported in [3].

In order to operate the battery cells within their specifications an idealized battery management system was modeled. This management system routes the energy between the wind farm, the households, the battery and the grid. The aim of the strategy of the battery management is to minimize the energy taken from the grid. As it is an idealized model, the battery management system is able to store and extract any given power to- and from the grid or battery. It also works without any losses. In addition it does not model any complex power system charging techniques, such as switching between current- and voltage based charging.

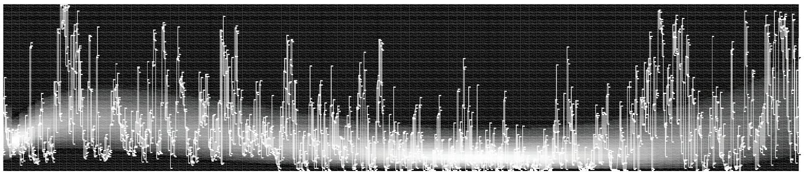

Figure 2: Wind power supply over one year (Jan-Dec) with fitted time carrying probability distribution. Clear seasonal effects visible.

2.2. Battery cell model

The basic battery cell model is based on the work of Trembley et al.[4,5]. They made use of the mathematical approach introduced by Shepherd in 1965 and enhanced it in order to solve the algebraic loop problem to approximate the cell voltage and state of charge. It allows switching between different battery chemistries, which expands the use of the model. The model was remodeled in Simulink (Mathworks, MA), in order to be able to implement aging and capacity loss of the battery.

Li-Ion battery model by Tremblay et al.:

$$V_{Batt,discharge} = E_0 - R \cdot i - K \frac{Q}{Q - it} \cdot (it + i^*) + A \cdot e^{(-B \cdot it)} \quad (1)$$

$$V_{Batt,charge} = E_0 - R \cdot i - K \frac{Q}{it - 0.1 \cdot Q} \cdot i^* - K \frac{Q}{Q - it} \cdot it + A \cdot e^{(-B \cdot it)} \quad (2)$$

The equations (1) and (2) show the battery voltage calculation for both charge and discharge. E_0 represents the battery constant voltage, R is the internal resistance, Q equals the battery capacity, i is the battery current, i^* the filtered current, it the integrated current and K, A and B are shape parameters that can be retrieved from the discharge curve given in the manufacturers spec sheet. Figure 3 shows the implementation of the discharge model in MATLAB Simulink.

The assumptions made by Tremblay et al. also apply in this context:

- The internal resistance is supposed constant during the charge and discharge cycles and doesn't vary with the amplitude of the current
- The model's parameters are deduced from the discharge characteristics and assumed to be the same for charging.
- The capacity of the battery doesn't change with the amplitude of the current (no Peukert effect)
- The temperature doesn't affect the model's behavior.
- The self-discharge of the battery is not represented.

- The battery has no memory effect.

Since the memory effect for LiFePO4 batteries only affects the battery behavior to a minor degree[6] the error made because of it can be neglected. The self-discharge of a LiFePO4 (5-8% per month[7,8]) is relatively low compared to the average currents and can thus be neglected as well. It is assumed, that the battery is stored in an air-conditioned environment at standard conditions of 20°C. Hausmann and Depcik introduced the battery cell specific constant α, which is analogue to the Peukert exponent and showed, that the value for modern LiFePO4 batteries lies around 1.03 which is very low in comparison to lead-acid batteries (about 1.4), which means the capacity change due to the amplitude of the current is small[9]. Thus the assumption made by Trembley et al. are valid for the battery cell type used and only leads to relatively small errors.

The limitations of the model, that describe the minimum and the maximum no-load battery voltage as well as the no-load minimum and maximum capacity have no effect in this context, since the battery management system does not allow overcharging or discharging below DOD.

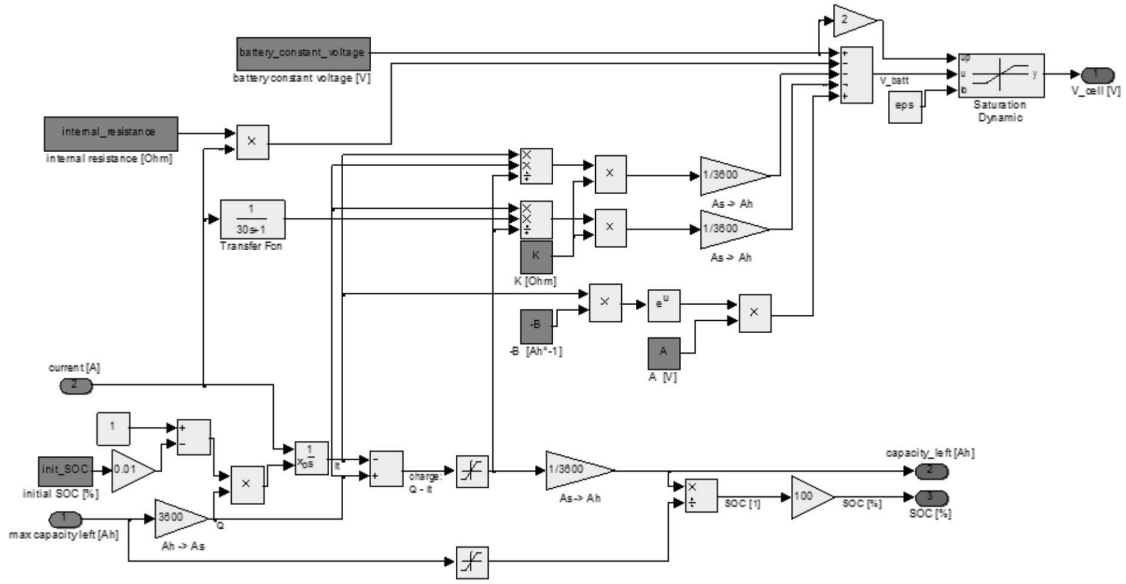

Figure 3: Implementation of the battery cell discharge model in MATLAB Simulink

The battery cell type used in this examination is a currently purchasable high power LiFePO4 battery cell with a high cycling durability. The parameters were extracted as proposed by Tremblay et al.[5]. Figure 4 shows the discharge characteristics for different discharge rates that were achieved using the extracted parameters.

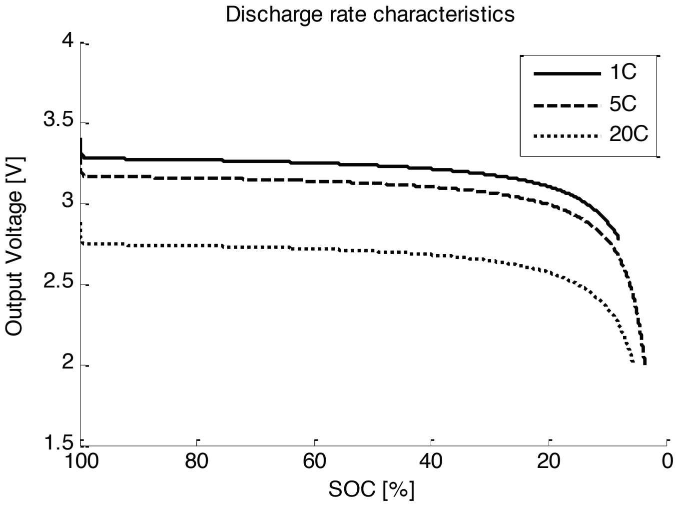

Figure 4: Simulated discharge curves

2.3. Battery aging model

The battery aging model is an Ah-throughput based model. It is assumed, that the battery can endure a certain Ah-throughput before the EOL (usually 80% of the capacity left) is reached. This total throughput can be described in the following simplified manner:

$$C_{Total} = 2 \cdot n_0 \cdot Q_0 \cdot \frac{DOD_0}{100} \tag{3}$$

In this case $n_0$represents the count of cycles the manufacturer specifies as cycle life (before EOL is reached), Q_0 is the nominal battery capacity and $DOD_0$is the depth-of-discharge the manufacturer used during cycle life testing.

Thus the state-of-health (SOH) can be described as (see Figure 5 for graphic representation):

$$SOH = 100 \cdot \frac{C_{Total} - \int I\,dt}{C_{Total}} \tag{4}$$

Depending on the SOH a function was implemented in order to reduce the maximum capacity of the battery cells. This function is based on the work of Stöcklein[10], but directly uses the SOH instead of the number of cycles:

$$C(t) = C_N - \Delta C \cdot e^{-p_1 \cdot (SOH)} \tag{5}$$

In this context $C(t)$ represents the capacity the full battery cell has left, ΔC is the capacity loss at the end-of-life and p_1 is a shape factor (usually $p_1 = 5$).

The temperature is not taken in account in the aging model either, for the same reasons that were stated earlier.

Also the impedance rise of the battery is not represented, since there is few reliable data on that topic for LiFePO4 battery cells. Also both the currents (average: below C/2, maximum: around 1C) and the internal resistance are relatively low, so the effect on the results is small as well.

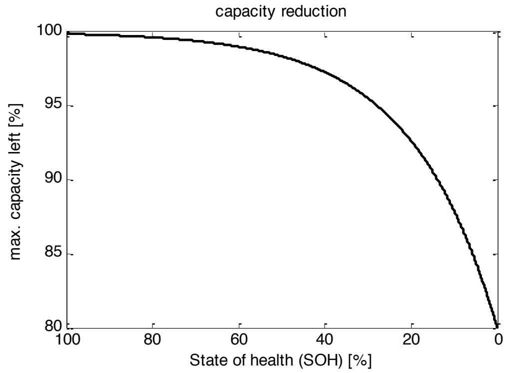

Figure 5: Capacity reduction as a function on the state of health (SOH)

2.4. Parameter variation

In order to be able to make statements on the battery aging as a function of the battery size as well as the load variability a large number of simulations were run. The battery size was varied from 20 to 650 ADPh. The load variability has three different states (low, medium, high) representing a lower or higher correlation between the energy consumption habits of the individual households. Each simulation run represents three years of battery use. As references, additionally a constant load, a sinusoidal load as well as a sawtooth load were used.

3. Results

The basic result of the paper is to estimate the SOH of the battery (at different sizes) after 3 years of operation (effects of further operation beyond 3 years may be estimated using Figure 5, by converting to capacity loss).

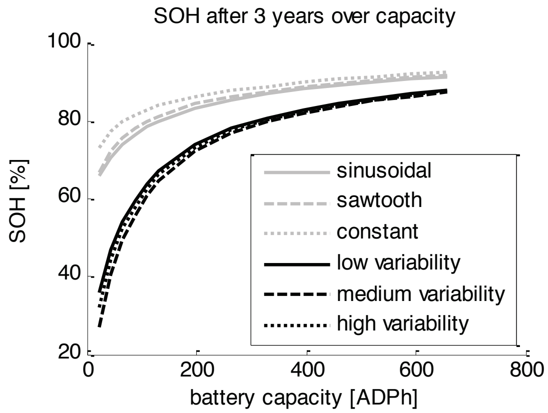

Figure 6: SOH after 3 years of cycling over different battery capacities

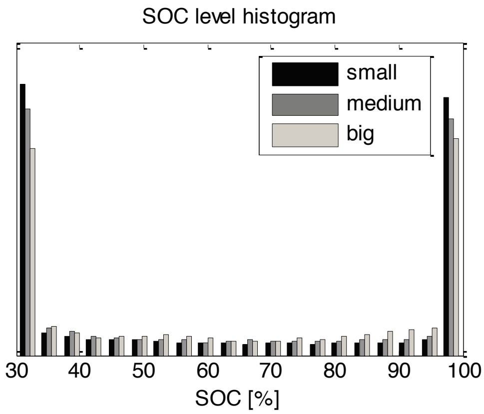

Figure 7: Histogram of SOC over time for three different battery sizes at domestic load with high variability

In Figure 6 the influence of the battery capacity on the SOH after three years of use is displayed. First thing one can see, is that the artificial loads (sinusoidal, sawtooth, constant) have a lower impact on the SOH of the battery then the more realistic, stochastic loads. Whereas a 75% SOH after 3 years with a 200 ADPh battery can be retained, this requires a roughly 4 times larger battery than that calculated using deterministic load variations. Secondly the variability of the stochastic loads has a slight impact on the SOH as well. Apart from that, independently from the load cycle, there is a region of high sensitivity for the capacity of 200 ADPh and below, under which the battery ages at a rate inversely proportional to its size. Since this region of high slope does not depend on the load, it is assumed, that the supply, which was equal for all simulations, is responsible for this (albeit at different SOH rates).

Figure 7 shows the SOC distribution over time for three different battery sizes. For the small battery the distribution shows, that at most states the battery is either full or at minimum charge, which should be viewed no only as a physical necessity but also as a safety factor in case of extreme events. The bigger the battery the more time it spends either at intermediate charge levels.

4. Conclusions

Whereas batteries are often rated using tests derived from industrial equipment rating (e.g. sawtooth profiles) storage components for smart-grids should more realistically be rated for stochastic load and charge cycles. The combination of deterministic (and synchronized) charge and load cycles have not been reported, since they would be equivalent to constant charge and deterministic load, which is a highly unlikely scenario (and one which leads to longer life ratings). Where both charge and load are stochastic (and unsynchronized) the batteries in a given scenario require higher size ratings than might seem apparent (by an approximate factor of 4) from standard ratings, and having approximately 2 weeks equivalent of average household consumption (ADC) would suffice to keep the SOH above 75% even after 3 years of operation. While the overall variability of load cycles we've looked at it similar, the effect they have (relative to battery size) on the shape of distribution of the state of charge is significant, suggesting that the entropy of SOC distribution is a key factor in proper gaging of operational life requirements.

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